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Corrosion Potential Prediction of Medical Bio-Magnesium Alloys Based on Stacking Integrated Learning

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ABSTRACT. *The corrosion behavior of biodegradable magnesium alloys when implanted in the human body is a critical factor affecting the safety and effectiveness of the implant. Accurate prediction of the corrosion potential is essential for optimizing the degradation rate of these alloys in vivo. This study presents a novel predictive model, "CorroStack-LGBLSTM", which employs a stacking ensemble learning approach to forecast the corrosion potential of medical bio-magnesium alloys. The model is composed of a two-tier learner system; the primary learner combines the strengths of XGBoost and LightGBM to handle the complexities of irregularly structured data, while the secondary learner utilizes LSTM networks to identify and incorporate time-series patterns and long-term dependencies within the data. Through a rigorous process of data preprocessing, feature selection, and model training, the "CorroStack-LGBLSTM" model has demonstrated significant performance advantages in predicting corrosion potential, achieving a mean square error of* 0.015 *and an impressive coefficient of determination of* 0.98*. This indicates the model's high accuracy and reliability in forecasting tasks. The study not only provides a new method for predicting the corrosion behavior of medical bio-magnesium alloys but also contributes to the broader field of material science by showcasing the power of integrated learning models in handling complex, multivariate problems. The findings of this research could have significant implications for the design and application of next-generation biodegradable magnesium alloys in medical implant technologies.*
Keywords: stacking integrated learning; medical bio-magnesium alloys; corrosion potential prediction; XGBoost; LightGBM.

1. **Introduction.** With the rapid development in the field of biomaterials, magnesium and its alloys, as an ideal biodegradable material, are increasingly attracting extensive attention from both academia and industry. With the rapid development of biomaterials, magnesium and its alloys, as an ideal biodegradable material, have attracted more and more attention in the academic and industrial fields because of their excellent Biocompatibility and degradability. With excellent biocompatibility and biodegradability, magnesium alloys have shown great application prospects, especially in the field of medical implants, such as bone fixation devices and vascular stents [1]. These materials are able to degrade naturally in the body without the need for secondary surgical removal, significantly reducing postoperative pain for patients. However, the rapid corrosion behaviour of magnesium alloys in body fluids is one of the main challenges in their application, and excessive corrosion can lead to a rapid reduction in the structural strength of the implant, affecting its biological function [2]. Therefore, how to accurately predict the corrosion potential of medical bio-magnesium alloys and thus optimise their degradation rate in vivo has become a focus of attention for researchers [3].

The prediction of corrosion potential, as a key parameter reflecting the corrosion process of a material, helps to assess the corrosion resistance of a material, which in turn provides a basis for the design and development of high-performance magnesium alloy materials [4]. However, the corrosion process is affected by a variety of factors, such as material composition, microstructure, environmental conditions, etc., resulting in the prediction of corrosion potential becoming a complex multivariate problem. Therefore, how to effectively predict the corrosion potential of magnesium alloys by combining multiple influencing factors through advanced data-driven methods has become a current research hotspot in the field of biomaterials.

1.1. **Related work.** Over the past few years, machine learning has spurred the adoption of data-driven methods for predicting material properties, gaining traction in the field of materials science [5].

By constructing data models, researchers are able to mine complex nonlinear relationships from experimental data to achieve accurate predictions of material behaviour. Researchers in the realm of medical magnesium alloy corrosion potential have explored various machine learning techniques to establish predictive models. These include linear regression, support vector machines (SVMs), and decision trees, aiming to correlate alloy corrosion potential with influencing factors [6]. These models have improved the accuracy of prediction to some extent, but most of them suffer from overfitting or insufficient generalisation ability, which makes it difficult to cope with complex material systems and diverse experimental conditions.

Integrated learning methods show high robustness and performance in dealing with complex problems. Especially, ensemble methods like XGBoost and LightGBM are gaining popularity in predicting material properties [7]. These methods excel at managing complex data and offer efficient training processes. XGBoost has remarkable results in handling high-dimensional and heterogeneous data, while LightGBM is able to quickly process large-scale data and reduce computational costs through an efficient gradient boosting framework. However, although these models are effective in capturing patterns in complex data, they still have limitations in their performance when dealing with time-series data or problems that need to consider long time dependencies.

To tackle this challenge, numerous studies leveraging deep learning have surfaced, with LSTM networks being particularly prominent [8]. They excel at modeling time series data and capturing long-term dependencies, thanks to their unique architecture. LSTM are able to efficiently memorise and make use of the historical information through its gating mechanism, thus enhancing the prediction performance on time series or dependent data.

In response to the complexity of predicting magnesium alloy corrosion potential, this study introduces a novel predictive model that harnesses a stacked ensemble learning approach. By integrating the strengths of XGBoost, LightGBM, and LSTM, the model is designed to analyze intricate nonlinear data relationships. XGBoost and LightGBM serve as the initial learners to identify key patterns, while LSTM acts as a secondary learner to refine predictions by unearthing significant temporal dynamics within the data [9]. This integrated strategy aims to enhance the accuracy of corrosion potential forecasts for magnesium alloys.

1.2. **Contribution.** The "CorroStack-LGBLSTM" model represents a significant advancement in the field of predictive analytics for medical bio-magnesium alloys. This model pioneers a novel stacking integrated learning strategy that synergizes multiple algorithms to enhance the accuracy of corrosion potential predictions. At its core, the model employs XGBoost and LightGBM as primary learners, leveraging their prowess in handling complex and irregularly structured data. These algorithms are chosen for their ability to efficiently process different feature distributions, a capability that is crucial for capturing the nuances of corrosion behavior. The model is further augmented by the inclusion of LSTM as a secondary learner, which introduces a deep understanding of time-series data. This allows the model to not only identify immediate fluctuations but also to discern long-term trends and underlying patterns that may not be apparent in snapshot analyses. The integration of LSTM is particularly innovative as it enables the model to consider the impact of historical data on current corrosion potential, thus enhancing the model's predictive power and responsiveness to changes over time.

Moreover, the model employs an adaptable feature processing method that is tailored to handle the intricacies of irregular data. This method capitalizes on the distinct strengths of XGBoost and LightGBM, ensuring that the model can adapt to varying data structures and improve the reliability of its predictions. By effectively amalgamating the strengths of these algorithms, the "CorroStack-LGBLSTM" model sets a new standard for precision in corrosion potential forecasting for medical-grade bio-magnesium alloys. This innovative approach has the potential to significantly influence the design and application of these alloys in the development of safer and more effective medical implants.

2. Theoretical analysis.

2.1. XGBoost algorithm.

XGBoost is a gradient boosting-based ensemble learning algorithm that excels in handling complex data and has delivered strong results in numerous machine learning contests [10]. XGBoost is a Boosting method that enhances model accuracy iteratively by integrating multiple weak learners, typically CART decision trees. In each iteration, XGBoost fits the previous round of prediction errors (residuals) to gradually approximate the true value, thus reducing the prediction bias.

XGBoost aims to optimize a loss function that incorporates regularization. This function has two components: one that assesses the prediction error relative to actual values, and another that regulates model complexity to avoid overfitting [11].

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{1}$$

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{2}$$

In the context of XGBoost, the objective function to be minimized encompasses both the predictive error relative to actual outcomes and a regularization component. This function takes into account the loss associated with each individual observation, the total count of leaf nodes (T), the magnitude of the weights assigned to these nodes (w_j), and the regularization parameters (γ and λ) which are crucial for avoiding excessive model complexity.

The essence of the algorithm involves creating successive decision trees, each targeted at the prediction errors from the prior iteration. This iterative process fine-tunes the model, gradually honing in on the true values and enhancing the model's ability to identify intricate patterns and extract features from sophisticated datasets. When building each tree, XGBoost selects the best split point by maximising the gain of the objective function. The gain function is calculated based on the loss reduction of each leaf:

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma \tag{3}$$

where G_L and G_R represent the gradient sums for the left and right branches, respectively. Similarly, H_L and H_R denote the second-order gradient sums for these branches. The term λ serves as the regularization parameter, while γ is the penalty imposed on leaf nodes.

XGBoost optimises the model iteratively by gradient boosting. In each round, the residuals of the previous round's predictions are fitted:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i) \tag{4}$$

where $\hat{y}_i^{(t)}$ represents the predicted value after the tth iteration. The learning rate is denoted by η, which determines the extent of each update step. Additionally, $f_t(x_i)$ signifies the prediction made by the tth tree for the ith data sample.

XGBoost employs a second-order Taylor expansion to approximate the loss function efficiently, thereby simplifying the computation of the objective function:

$$\mathrm{L}(\theta) \approx \sum_{i=1}^{n}\left[g_i f(x_i) + \frac{1}{2}h_i f(x_i)^2\right] + \Omega(f) \tag{5}$$

where g_i represents the first-order derivative, or gradient, of the loss function, indicating the discrepancy between the model's current prediction and the actual value. Meanwhile, h_i denotes the second-order derivative, which quantifies the loss function's curvature.

Utilizing a second-order Taylor expansion, the model considers both the gradient and the Hessian of the loss function, which accounts for not just the slope but also the curvature. This dual consideration enhances the stability and precision of the optimization process.

XGBoost incorporates L1 and L2 regularization terms, enabling the control of model complexity. By tuning these hyperparameters, the model can be prevented from overfitting. In addition, XGBoost introduces pre-pruning and post pruning strategies when constructing the decision tree, which improves the computational efficiency by calculating the gain when splitting the nodes and stopping the invalid splits in advance.

2.2. **LightGBM algorithm.** LightGBM is an efficient gradient boosting framework that utilizes decision trees. In the "CorroStack-LGBLSTM" model, LIGHTGBM is used to process large-scale data sets quickly, and we adopt its unique feature packaging technology to improve the efficiency of model training and prediction performance. It employs a histogram-based approach for tree construction, leveraging a Leaf-wise growth strategy [12]. Additionally, it incorporates innovative techniques like exclusive feature bundling and histogram differencing, which significantly enhance both training efficiency and predictive performance.

LightGBM employs a histogram-based approach to discretize continuous floating-point features into k distinct bins, creating a histogram of width k. It traverses the training dataset to compute the cumulative statistics for each bin and identifies the most effective split points within the histogram based on these discrete values, as illustrated in Figure 1.

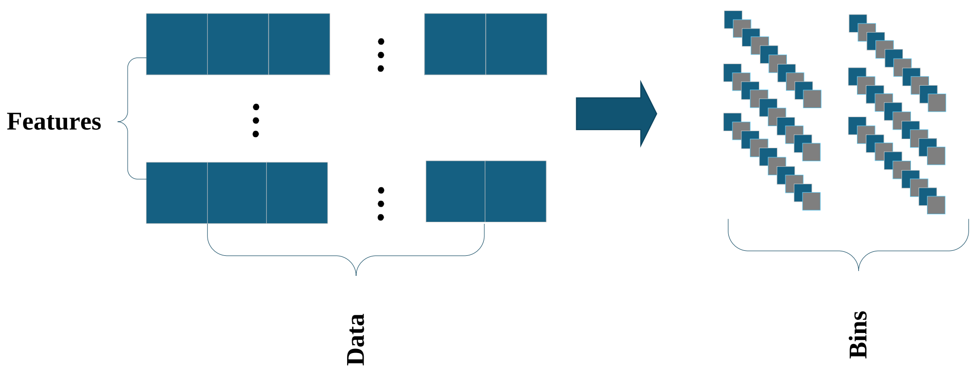

Figure 1. Illustration of the Histogram Algorithm's Workflow

LightGBM minimizes computational complexity through the use of histograms, which involve segmenting continuous features into multiple buckets, each encompassing a specific value range [13]. The model quickly finds the split point with the largest split gain by counting the cumulative gradient and second-order gradient within each bucket.

$$H(x) = \frac{\partial^2 L}{\partial w^2} \tag{6}$$

where $H(x)$ represents the second-order gradient of the objective function. It is utilized to assess feature splitting and efficiently identify the optimal split point that maximizes gain, based on the cumulative statistics.

LightGBM employs a leaf-wise growth strategy, which constructs decision trees in a more computationally efficient manner [14]. This approach focuses on expanding one leaf at a time, prioritizing the leaf that offers the greatest potential for reduction in loss (i.e., the largest splitting gain) and contains a substantial amount of data. This process continues, with each subsequent split targeting the most beneficial division of data. However, to mitigate overfitting, it's crucial to manage the tree's depth and ensure that each leaf node maintains a minimum quantity of data. This strategy is visualized in Figure 2.

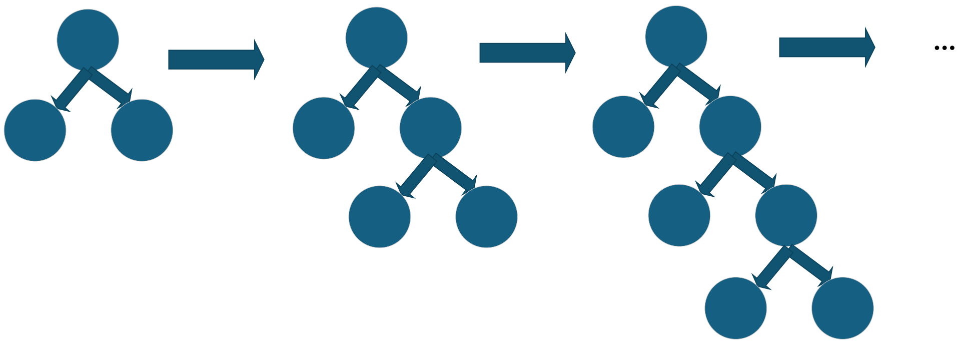

Figure 2. Overview of the Leaf-wise Growth Strategy

To further improve efficiency, LightGBM also introduces techniques such as mutually exclusive feature bundling and histogram differencing. In large-scale datasets with high feature dimensions, LightGBM employs mutually exclusive feature bundling to combine features that rarely occur simultaneously. This strategy effectively reduces the total number of features, thereby simplifying the model's complexity. Additionally, the histogram difference technique accelerates computational speed. It leverages the histogram of the parent node to rapidly determine the histogram for child nodes, eliminating the need to re-scan the data with each iteration.

LightGBM, like other GBDT models, optimises the loss function with the goal of minimising the error while controlling the complexity of the model through the regularisation term [15]:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \lambda \sum_{j=1}^{T} |w_j| \tag{7}$$

where $l(y_i, \hat{y}_i)$ represents the error loss, while λ is the regularization coefficient, and w_j denotes the weights assigned to the leaf nodes. Through regularization, the model mitigates the risk of overfitting, particularly enhancing its generalization capabilities when processing complex datasets.

2.3. **LSTM algorithm.** LSTM is a type of deep learning model that excels at handling time-series data. It utilizes memory cells and gating mechanisms to effectively capture long-term dependencies [16]. The flow of information within the neurons is controlled by forget gates, input gates, and output gates [17]. This control helps prevent issues like gradient vanishing or gradient explosion, leading to superior performance in processing sequential data.

The forget gate is responsible for deciding which information to discard at the present time step. Its value is determined by the following formula:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{8}$$

The output of the forgetting gate, f_t is determined by a weighted combination of the previous hidden state h_{t-1}, the current input x_t, and the bias term b_f, all passed through a sigmoid activation function. This function, denoted by σ, constrains the output to a range between 0 and 1. The weight matrix associated with the forgetting gate is W_f.

The input gate is responsible for deciding which new information to store at the current time step. This determination is made using the following formula:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{9}$$

The input gate's output, represented by i_t, is derived from the input gate's weight matrix W_i and bias term b_i.

The output gate is tasked with deciding which information to release at the current time step. The formula for this calculation is as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{10}$$

The output gate's output, denoted by o_t, is calculated using the weight matrix W_o and bias b_o associated with the output gate.

LSTM effectively addresses the gradient vanishing issue in sequential data by utilizing its gate mechanisms to capture crucial features within the dataset.

2.4. **Stacking model.** Stacking is an effective ensemble learning technique that enhances a model's generalization capabilities [18]. It achieves this by integrating the predictive outcomes of several base models. Unlike traditional Bagging and Boosting methods, instead of simply averaging or weighting the results of different models, stacking learns how to best fuse the outputs of these base models through a sub-model.

Stacking operates across two distinct layers [19]. The initial layer comprises multiple base models that are trained independently and generate predictions on the data. The subsequent layer involves a meta-model that utilizes the predictions from the first layer as new input features for further learning and forecasting. This approach has the advantage of mitigating the bias and variance associated with individual models by leveraging their combined predictions, thereby enhancing the overall predictive accuracy [20].

The development of a stacking model can be broken down into two primary phases:

Stage 1: Training multiple base models (e.g., XGBoost and LightGBM). These models learn the training set separately and output the prediction results for the target variables [21].

Set the training dataset to be X and the labels to be y. Assume that there are two base models f_1 and f_2, which make predictions about X. The output is:

$$\hat{y}_1 = f_1(X) \tag{11}$$

$$\hat{y}_2 = f_2(X) \tag{12}$$

The predictions of the base model will be used as new features to form a new training set X', i.e:

$$X' = [\hat{y}_1, \hat{y}_2] \tag{13}$$

Stage 2: The secondary model (LSTM) uses the predictions from the output of stage 1 as input for secondary learning. the LSTM generates the final prediction y_{final} by capturing patterns and features in the output of the base model.

$$y_{\text{final}} = f_{\text{LSTM}}(X') \tag{14}$$

With this design, the secondary model can effectively learn the prediction errors and non-linear features of the base model to further optimise the model performance.

To prevent overfitting of the stacking model, different training data are used for the primary and secondary models. Typically, a portion of the original dataset is used for training the primary model, while the remaining data or results from cross-validation are used for training the secondary model. By dividing the data in this way, the model is able to avoid overfitting a particular data distribution and has a stronger generalisation ability when dealing with unknown data.

In our research, the base models, XGBoost and LightGBM, produce predictions using cross-validation. These predictions are then input into an LSTM model, which integrates and further refines them to create the final corrosion potential forecasting model.

3. Multi-algorithm fusion of corrosion potential prediction model for medical magnesium alloys: CorroStack-LGBLSTM.

3.1. Model structure.

In this study, the stacking model consists of two layers of learners. The primary learner uses XGBoost, which is more effective in dealing with irregular data, and LightGBM, which has outstanding efficiency performance. These two models have their own advantages in dealing with different feature distributions and data structures, and by combining them, the primary learner is able to generate more diversified and comprehensive prediction results.

On this basis, the secondary learner adopts the LSTM deep neural network. LSTM excel at identifying both long-term trends and immediate fluctuations within time series data, effectively extracting crucial patterns and features. Therefore, LSTM, as a secondary learner, is not only able to further process the output of the primary learner, but also able to identify the implicit time series patterns and complex nonlinear relationships, which ultimately improves the overall prediction ability of the model.

(1) Primary learner: Combination of XGBoost and LightGBM. The primary learner's role is to distill initial features directly from the raw data. XGBoost and LightGBM are able to automatically recognise the importance of the features when processing the data and generate tree-based feature representations through their respective learning mechanisms. Subsequently, the outputs of these two models are combined into a new feature set that forms the input to the secondary learner.

The integration of features is encapsulated in the equation that follows:

$$X_{stack} = f(X_{XGBoost}, X_{LightGBM}) \tag{15}$$

where X_{stack} is the fused feature set, f denotes the feature fusion function, and $X_{XGBoost}$ and $X_{LightGBM}$ are the outputs of the XGBoost and LightGBM models, respectively.

(2) Secondary learners: An application of the LSTM. The secondary learner LSTM is responsible for deep learning on the feature set generated by the primary learner [22]. LSTM, through its analysis of time series, can detect both extended and immediate data dependencies. The mechanism of updating its internal state can be described by the following equation:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{16}$$

$$h_t = o_t \odot \tanh(C_t) \tag{17}$$

In the context of LSTM networks, C_t denotes the cell's state at the present time step. The forgetting gate's output is represented by f_t, determining which information to discard or retain. Meanwhile, i_t signifies the input gate's output, responsible for generating a new candidate value for the cell state. Lastly, h_t corresponds to the hidden state at the current moment, which is used for further processing or as output in the network.

With this structural design, the "CorroStack-LGBLSTM" model achieves effective extraction of features by primary learners and in-depth analysis of complex patterns by secondary learners, thus comprehensively improving the accuracy of corrosion potential prediction [23].

3.2. **Modelling workflow.** The "CorroStack-LGBLSTM" model's operational sequence encompasses several distinct stages: The operation sequence of the "CorroStack-LGBLSTM" model consists of several different stages: Data pre-processing, primary learner training, secondary learner training, and model prediction.

(1) Data preprocessing: Initially, the dataset is scrutinized for any missing entries and extreme values. Missing entries are subsequently imputed with either the mean or median, while outliers are detected using the Z-score method and addressed accordingly [24]. Finally, all features undergo normalization to a distribution with a mean of 0 and variance of 1, which aids in accelerating the model's convergence.

(2) Primary Learner Training: The XGBoost and LightGBM models are trained using preprocessed data to generate predictions for each sample. These predictions are used as new features that form the input to the secondary learner.

(3) Secondary learner training: The prediction results from the primary learner are input to the LSTM model for training. By analysing these results, the LSTM is able to learn deeper patterns and time series features [25].

(4) Model Prediction: In the testing phase, new data is fed into the primary learner to generate predictions, and then these results are fed into the LSTM model to produce a final corrosion potential prediction [26].

4. Performance testing and analysis.

4.1. **Data sets.** The dataset for this study was collected from corrosion experiments on medical bio-magnesium alloys and contains several characteristic variables related to corrosion potential. These variables cover ambient temperature, humidity, pH, alloy composition, and historical corrosion potentials. The dataset contains a total of 1000 samples, each labelled with the actual observed corrosion potential as the target variable for model prediction. The specific information is shown in Table 1:

Table 1. Data details

Feature Name	**Description**	**Unit**
Ambient Temperature (T)	Temperature during corrosion tests	°C
Ambient Humidity (H)	Humidity during corrosion tests	%
pH Value (pH)	pH level of the test environment	Dimensionless
Alloy Composition (C_i)	Content of different elements in the alloy	wt%
Historical Corrosion Potential (E_{corr})	Corrosion potential measured in past experiments	mV
Target Variable (E)	Corrosion potential to be predicted	mV

4.2. **Experimental Procedure.** Firstly, the input data were cleaned and standardised to ensure data quality. At the same time, the feature variables are converted into a format suitable for XGBoost and LightGBM model training.

The Pearson correlation coefficient is employed to measure the strength of association between individual features and the outcome variable. Subsequently, features demonstrating significant correlations are chosen for inclusion in the model.

We employed stratified sampling to partition the dataset, ensuring that the representation of target variables was uniform across both the training and testing subsets. The allocation was such that 70% of the data formed the training subset, dedicated to model development and optimization, while the remaining 30% constituted the test subset, reserved for the ultimate assessment of the model's performance.

Immediately after that the primary learners (XGBoost and LightGBM) are trained to optimise the hyper-parameters using a 5-fold cross validation method.

The predictions of the primary learners are fed as features into the secondary learners (LSTM) for training. The LSTM network is trained using serial data in the form of time series features transformed into a suitable input format.

The model's accuracy is gauged using two standard statistical measures: one that quantifies the average squared difference between predicted and actual values, and another that indicates the proportion of the variance in the dependent variable that's predictable from the independent variables. The formulas for these metrics are outlined below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{18}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{19}$$

where y_i represents the observed corrosion potential for each sample, while the model's corresponding predictions are denoted by $\hat{y}_i$. The total number of samples is given by n, and the mean of the observed corrosion potentials is represented by $\bar{y}$.

Once the model training was finalized, we proceeded to make predictions on the test set. The outcomes are illustrated in Figure 3.

The findings from our experiments indicate that the "CorroStack-LGBLSTM" model outperforms standalone XGBoost and LightGBM models on the test dataset. It achieves a notably lower mean squared error of 0.015 and a high R-squared value of 0.98, demonstrating its superior predictive capabilities. This result validates the effectiveness of the stacking integrated learning framework in improving the accuracy of corrosion potential prediction.

In addition, we compared the performance difference between the "CorroStack-LGBLSTM" model and the traditional regression model. As depicted in Figure 4, the performance metrics for conventional models like linear regression and decision tree regression on the dataset are markedly inferior to those of the "CorroStack-LGBLSTM" model. This comparison underscores the enhanced predictive performance of the model presented in this research.

Finally, we also performed an importance characterisation. The feature importance assessment revealed that ambient temperature, alloy composition and pH contributed the most to the prediction of corrosion potential. The significance of various features was determined by analyzing the XGBoost model's output, with the findings graphically represented in Figure 5.

By assessing feature importance using the XGBoost model, it was determined that ambient temperature, alloy composition, and pH are the primary factors influencing the prediction of corrosion potential. This finding provides important reference information for the design and application of future medical bio-magnesium alloys.

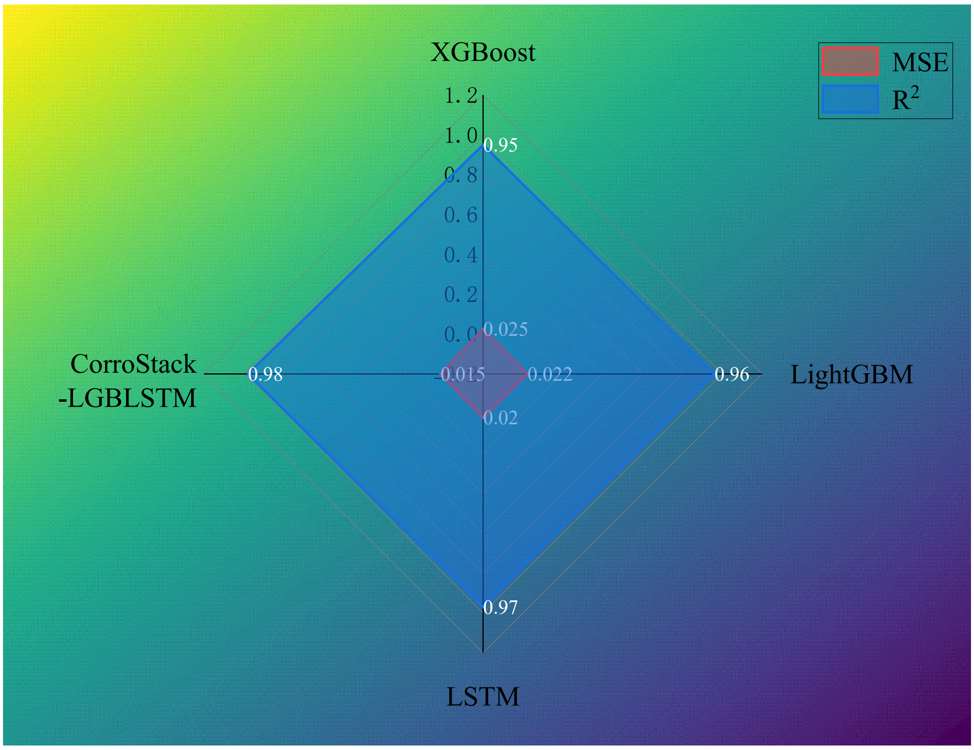

Figure 3. Model training results

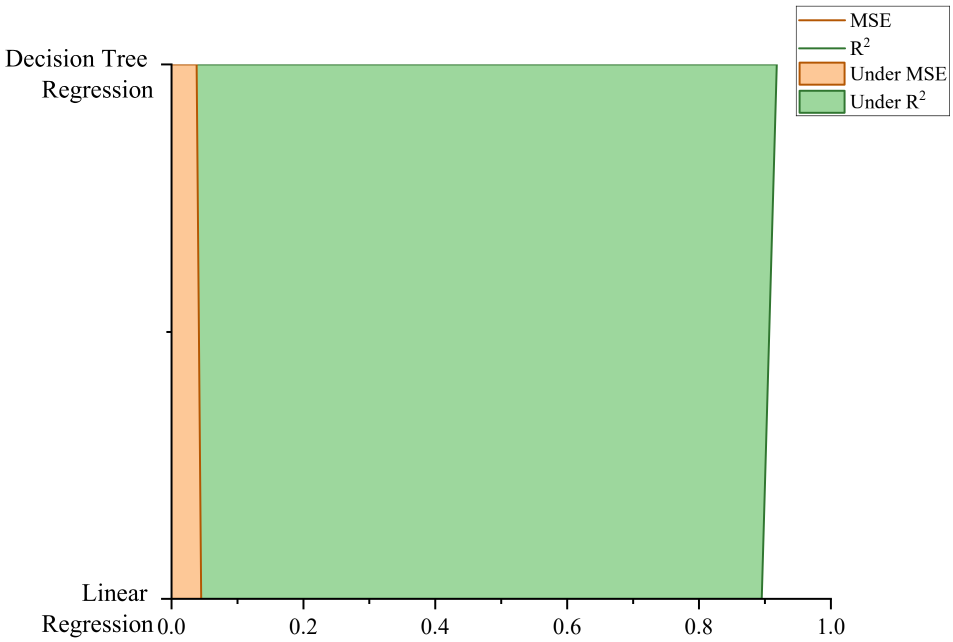

Figure 4. Comparative experimental results

5. **Conclusion.** In this study, a "CorroStack-LGBLSTM" model based on stacking integrated learning is constructed to effectively achieve the prediction of corrosion potential of medical bio-magnesium alloy. Leveraging the strengths of XGBoost and LightGBM, the primary learner adeptly manages complex data patterns. The combination of XGBoost

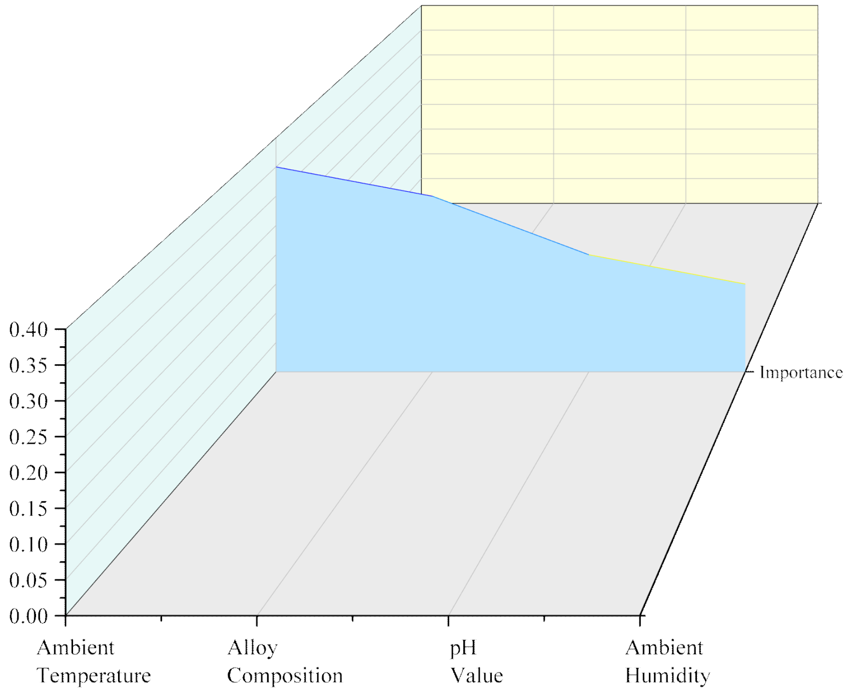

Figure 5. Results of experiments on the importance of characteristics

and LightGBM provides powerful data processing capabilities for the model, especially when dealing with irregular data structures, which is critical in the early learning stages of the model. Meanwhile, the LSTM as the secondary learner boosts the model's capacity to discern temporal features within the data. The experimental results fully validate the effectiveness of the stacking method in the field of materials science.

Despite the achievements of this study, there are still some limitations. Initially, the dataset's limited size and feature set could restrict the model's ability to generalize effectively when predicting outcomes for new samples. Second, the feature selection relies heavily on empirical methods, potentially overlooking some crucial variables. This could impact the model's predictive accuracy. Moreover, the model's complexity raises the specter of overfitting, particularly with a limited dataset. This could hinder the model's adaptability to new data. Finally, this study failed to consider the application of real-time monitoring data, which is crucial in assessing the corrosion behaviour of biomagnesium alloys and needs to be taken into account in future studies.

Future research could explore the following directions in depth:

1. Expanding the dataset: Expanding the dataset with additional data on bio-magnesium alloys' corrosion across various environments and conditions will enrich its diversity and size. This enhancement is expected to bolster the model's generalization capabilities, ensuring robust predictive performance across a range of scenarios.
2. Improve feature selection methods: Enhance feature selection techniques by exploring more systematic approaches, such as automated feature engineering and deep learning-based feature extraction. These methods can uncover hidden influential factors, thereby increasing the model's predictive accuracy.
3. Explore other integrated learning methods: Investigate alternative ensemble learning techniques beyond stacking. Examine strategies like Bagging and Boosting, comparing their pros and cons to identify the optimal model configuration.

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